Application of the Neural Nets for Forecasting the Electricity Demand

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Abstract: In this paper is discussed the application of neural networks for time series forecasting. This was illustrated with a single hidden layer feed-forward network, which is the most widely used neural network for forecasting. Short-term load forecasts are required for the control and scheduling of power systems. The focus varies from minutes to several hours ahead.

Key Words: forecasting, neural network, time series, electricity demand, activity function, input, hidden layer, output

1. Introduction.
Forecasting is intrinsically intervened with decision-making. Forecasts serve their purpose by helping Decision-makers to make decisions about an uncertain future. Forecast errors generate costs to the decision-maker, to the extent that different forecasts command different decisions. [2]

Each forecasting problem has many unique features that make it difficult to provide guidelines that are universally appropriate.

Many methods have been used to make forecasts of the future. Forecasting methods are often classified as quantitative or qualitative. The difference between the two is the process by which forecasts are generated, not the results. Qualitative forecasting methods rely on one or more persons to generate forecasts without using mathematical models. Quantitative forecasting methods use historical data to forecast the future. The objective of these methods is to study past happenings in order to understand the underlying structure of the data and use that knowledge to predict future occurrences.

Time series forecasting involve projecting future values of a variable based on the past and current observations of the variable.

Quantitative forecasting methods can be classified into causal methods and time series methods.

Causal methods involve finding factors that relate to the variable being predicted and using those factors to predict future values of the variable. Causal methods include:

- Regression analysis
- Econometric models
- Other models

Designation of this paper is to present the application of the neural networks for time series forecasting. [1]

2. Problem formulation
Electricity-supply planning requires efficient management of existing power systems and optimization of the decisions concerning additional capacity. Demand prediction is an important aspect in the development of any model for electricity planning. The form of the demand depends on the type of planning and the accuracy that is required; hence it can be represented as an annual demand, a peak demand, or load duration curves like daily, weekly or annual.

Short-term load forecasts are required for the control and scheduling of power systems. The focus varies from minutes to several hours ahead. The predictions are required as inputs to scheduling algorithms for the generation and transmission of electricity. The load forecasts help in determining which devices to operate in a given period, so as to minimize costs and secure demand even when local failures may occur in the system. [3]
In this article will be discussed neural forecasting method of the electricity demand cooper mill.

To evaluate forecasting performance in this cooper mill, is used 1369 twenty-four-hour periods for electricity demand. The data covers the period from 1 January 2000 to 31 October 2003. The series is shown in Fig. 1. It should be take notice of that the electric consumption varies from 3622MWh to 6608MWh. For year 2001 it can be noticed that there is tendency for stability of electric consumption.

There is no information for the capacity of production for this period and for forecasting is used only time series for electricity demand.

The autocorrelation analysis on the time series of electricity consumption for twenty-four-hour period shows that there is not short-term variation of the value of electricity demand. The autocorrelation function decelerated from 0.969 to 0.880.

3. Problem Solution

The most widely used neural network for forecasting is single hidden layer feed-forward network. It consists of a set of $k$ inputs, which are connected to each of $m$ units in a single hidden layer, which, in turn, are connected to an output.

The output of the perceptron as a function of the input signals can be written:

$$y = \sigma\left(\sum_{i} w_{i}x_{i} - \theta\right)$$

where:
- $y$ is the output
- $x_{i}$ are the input signals
- $w_{i}$ are the neuron weights
- $\theta$ is the bias term (another neuron weight)
- $\sigma$ is the activity function

Possible forms of the activity function are linear function, step function, logistic function and hyperbolic tangent function.

In this case for activity functions are used: in hidden layer hyperbolic tangent function and for the output layer linear function. It was fixed that our neural net has two layers: three neurons in input layer and 1 in hidden layer.
The output has three elements: max value of the electricity consumption in the mourning, max value of the electricity consumption in the evening and twenty-four-hour period of electricity consumption in previous days (Fig3.). Each neuron in a certain layer is connected to each neuron of the next layer. There are no feedback connections. The neural network of this type can be understood as a function approximator.

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The network weights are adjusted by training the network. It is said that the network learns through examples. The idea is to give the network input signals and desired outputs. To each input signal the network produces an output signal, and the learning aims at minimizing the sum of squares of the differences between desired and actual outputs. From here on, we call this function the sum of squared errors.

The learning is carried out by repeatedly feeding the input-output patterns to the network. The training aims at minimizing the errors of the network outputs with regard to the input-output patterns of the training set. The success in this does not, however, prove anything about the performance of the network after the training. More important is the success in generalization. A network is said to generalize well, when the output is correct (or close enough) for an input, which has not been included in the training set.

A typical problem with network models is overfitting, also called memorization in the network literature. This means that the network learns the input-output patterns of the training set, but at the same time unintended relations are stored in the synaptic weights. Therefore, even though the network provides correct outputs for the input patterns of the training set, the response can be unexpected for only slightly different input data.

Generalization is influenced by three factors: the size and efficiency of the training set, the model structure (architecture of the network), and the physical complexity of the problem at hand. The latter of these can not be controlled, so the means to prevent overfitting are limited to affecting the first two factors.

The larger the training set, the less likely the overfitting is. However, the training set should only include input-output patterns that correctly reflect the real process being modeled. Therefore, all invalid and irrelevant data should be excluded. The learning process is usually performed on an epoch-by-epoch basis until the weights stabilize and the sum of squared errors converges to some minimum value. [5]

It was used for neural network learning time series of electricity consumption from 1.01.2000 to 29.06.2003 (1276 twenty-four-hour periods) and for checking the model 9 twenty-four-hour periods (from 1.08.2003 to 30.10.2003).

The forecast of electricity demand with neural network is shown in Fig.4 and Mean absolute percentage error (MAPE) function is shown in Fig.5.

The accuracy of the forecast can be considered as satisfactory (in 90% of the cases the mean absolute error is about 6%).
4. Conclusion

Short-term load forecasting plays an important role in power system operation and planning. Accurate load prediction saves costs by improving economic load dispatching, unit commitment, etc. At the same time it enhances the function of security control.

The forecasting of energy demand has become one of the major fields of research in electrical engineering. The industry requires forecasts with lead times that range from the short term (a few minutes, hours or days ahead) to the long term (up to 20 years ahead). Short-term forecasts, in particular, have become increasingly important since the rise of the competitive energy markets.

References: